Spatial Metadata for Remote Sensing Imagery

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Outline

- Intelligent Systems Project
- Spatial complexity
  - Fractal dimension
  - Autocorrelation indices
- Results
  - Global (whole image) characterization
  - Local texture analysis

Problem Statement

- As the geographical and temporal coverage, the spectral and spatial resolution, and the number of individual remote sensors increase, the sheer volume and complexity of available data sets will complicate management and use of the rapidly growing archive of earth imagery.
- Mining this vast data resource for images that provide the necessary information for climate change studies becomes more difficult as more sensors are launched and more imagery is obtained.

Goal and Objectives

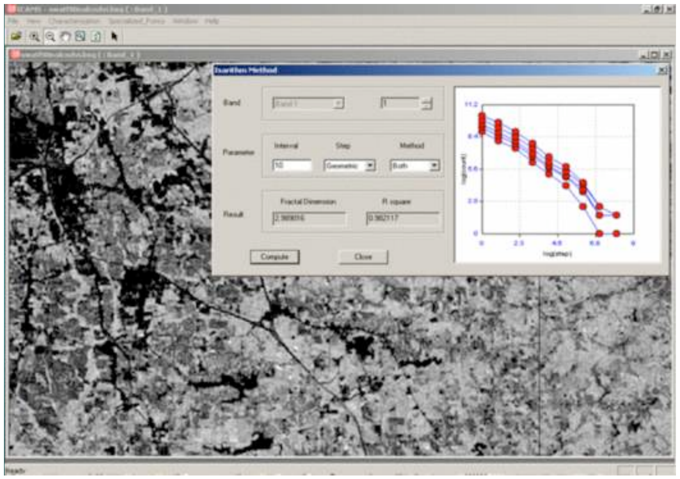
- Goal:
  - Improve global change studies by facilitating access to and improving analysis of remote sensing imagery
- Objectives:
  - Develop and test software applications and techniques for characterizing spatial complexity and content of images
  - Evaluate the utility of content-based image descriptors such as: fractal dimension, lacunarity, and spatial autocorrelation statistics in measuring and characterizing land covers and land-cover changes with a variety of multi-scale, multi-temporal, and multi-sensor data.

Schedule and Milestones

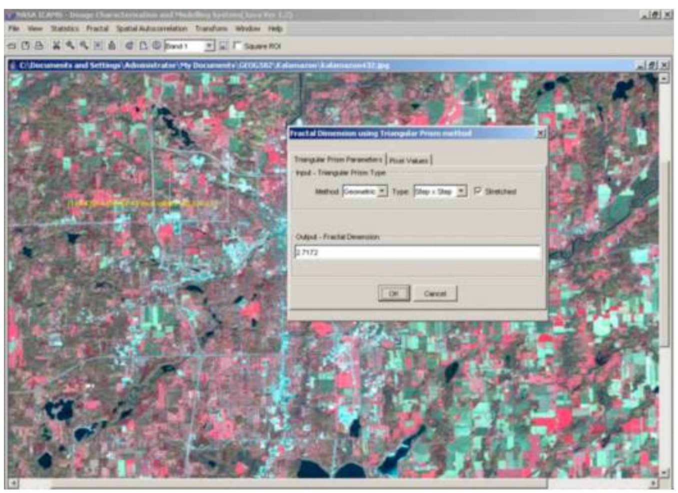
- Year 1 (6/01 _ 5/02):
  - Assemble imagery database;
  - Develop and implement global (whole image) fractal, lacunarity, wavelet and spatial autocorrelation algorithms
- Year 2 (6/02 _ 5/03):
  - Perform scaling sensitivity analysis of global spatial indices;
  - Develop and implement algorithms for local spatial analysis of imagery
- Year 3 (6/03 _ 8/04):
  - Perform analysis of land cover characterization capabilities;
  - Analyze effects of band ratioing, resampling, and other image processing procedures
  - Examine utility of spatial descriptors as search indices

ICAMS – Image Characterization and Modeling System

C++



Java Web Start



- Standalone and Java Web Start applications for spatial analysis of imagery
- Measures:
  - Fractal Dimension
  - Spatial Autocorrelation Indices
    - Moran’s I, Geary’s C, Getis’ G
  - Wavelet Signatures

Spatial Complexity and Texture

- Most remote sensing techniques that consider spatial structure are measures of image texture
  - Texture is the spatial arrangement of color and tone that form natural visual entities
- Texture analysis methods include:
  - Statistical methods
    - Local variance/standard deviation
  - Feature-based methods
    - Orientation, contrast (Gray-level co-occurrence), and spatial frequency (FFT and wavelets), join counts (Moran’s I)
  - Model-based methods
    - Fractals, Markov chains

Texture Data Sources

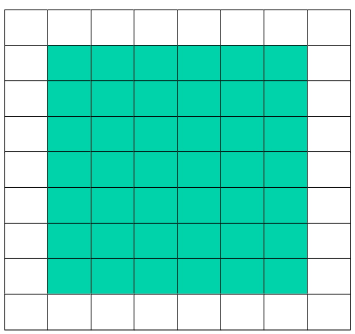
- Most modern optical remote sensors have a high resolution “Pan-sharpening” band in addition to lower resolution visible, near-infrared, and thermal infrared bands
  - SPOT
  - Landsat 7
  - Ikonos, Quickbird
- Statistical texture analysis methods require lots of pixels, so this resource is valuable as an input to determining overall image complexity
- Other analyses are possible
  - Individual bands
  - Principal components
  - Ratios (NDVI, etc.)

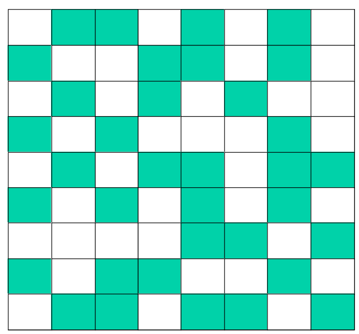
Fractal Dimension

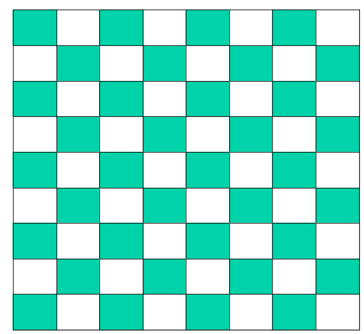
- True fractals are objects that are made of parts similar to the whole in some way—self-similarity
- Fractal Dimension: Non-integer and exceeds the topological integer dimension
  - Euclidean dimensions 0, 1, 2, 3 correspond to points, lines, areas, volumes
  - Fractal dimension for an image ranges from 2.0 for a flat plane to ~ 3.0 for a complex surface with bright and dark pixels closely adjacent
  - A problem with fractal dimension is that different textures can have similar fractal dimensions
- Lacunarity is a related concept that measures the homogeneity or heterogeneity of gaps in a pattern
  - Unlike fractals, which are based on the scale-independent concept of self-similarity, lacunarity varies with scale
  - It is a second moment to fractal dimension, so the ratio of lacunarity to fractal dimension may provide a more unique measure of texture

Moran's I Index of Spatial Autocorrelation

$$I = \frac{n}{\sum_{i=1}^{n}(z_i - \bar{z})^2} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(z_i - \bar{z})(z_j - \bar{z})}{2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}$$







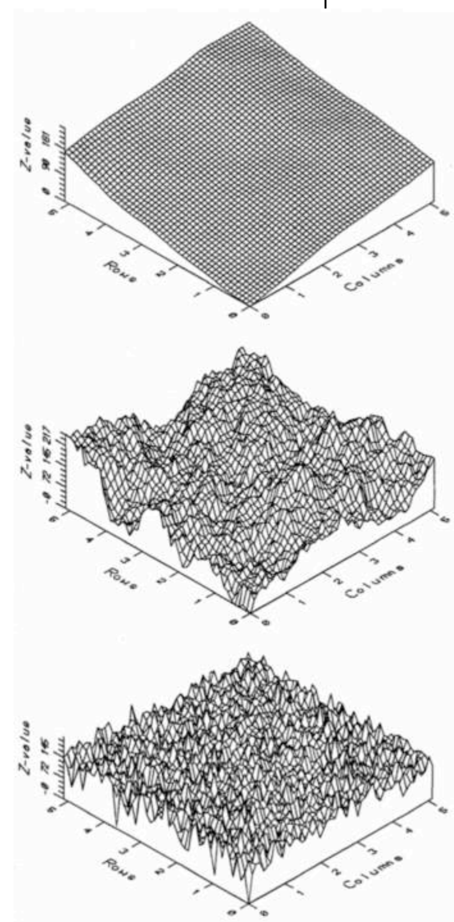
Clumped Pattern
I **≈ +1.0**

Random Pattern
I **≈ 0.0**

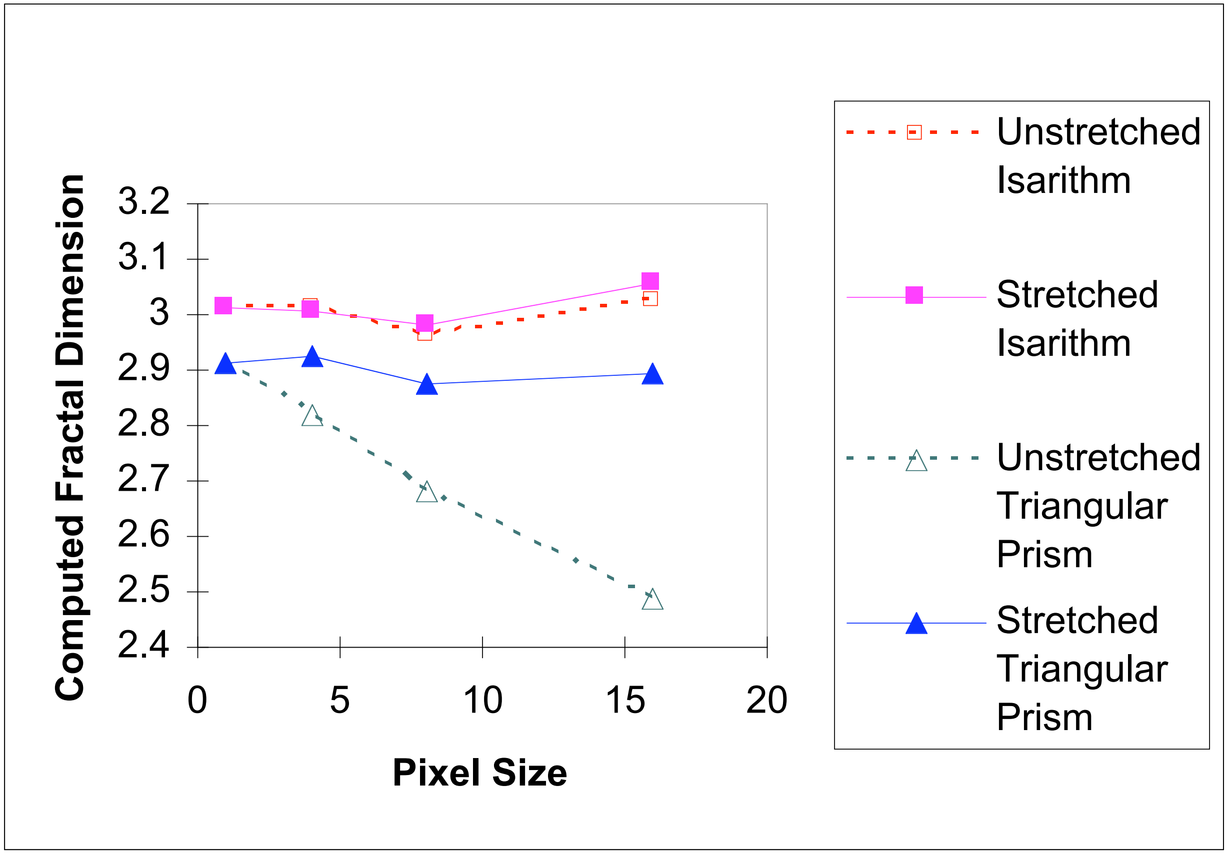
Dispersed Pattern
I **≈ -1.0**

Verifying Indices of Spatial Complexity

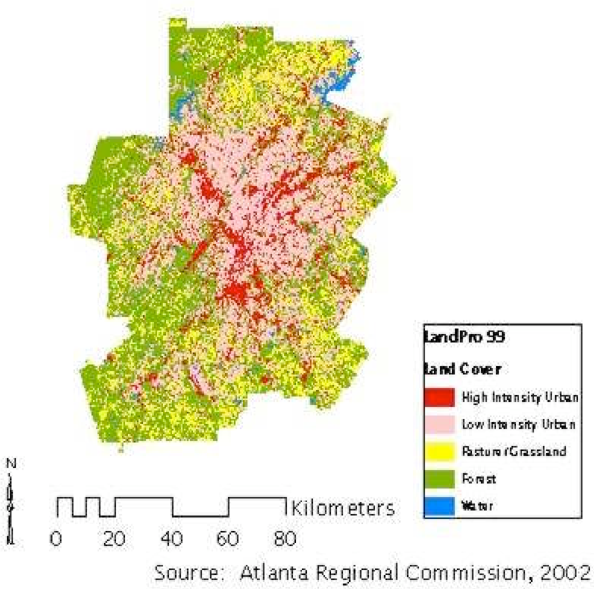
- Analysis of 25 simulated gray-scale surfaces with known fractal dimension
- 3 methods of measuring fractal dimension
  - Triangular prism, Isarithm, Semi-variogram
- Triangular prism measurement method is most accurate in the range of values commonly encountered in remotely sensed imagery (D = 2.6 - ~3.0)
  - This method is sensitive to contrast stretching
- Isarithm method is relatively robust, but has many input parameters and cannot effectively measure low dimension (smooth) surfaces
- Semi-variogram method of measuring fractal dimension is computationally expensive and relatively inaccurate

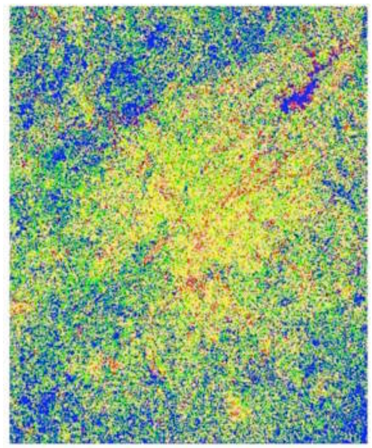


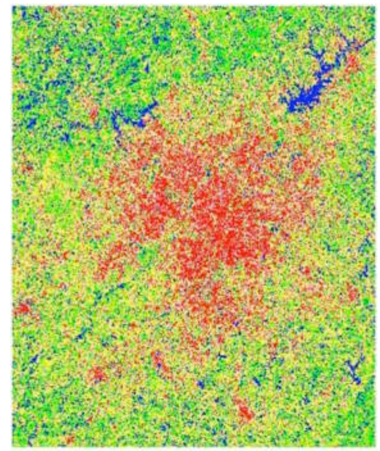
Effect of Contrast Stretching on the Isarithm and Triangular Prism Methods

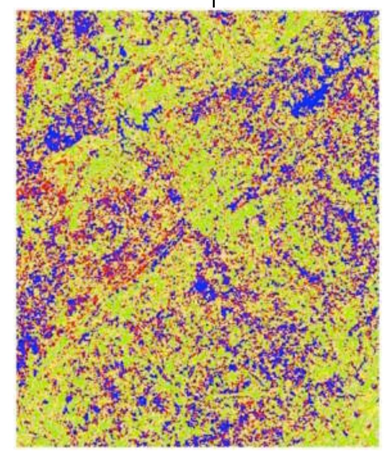


Comparison of Spatial Indices for Image Classification



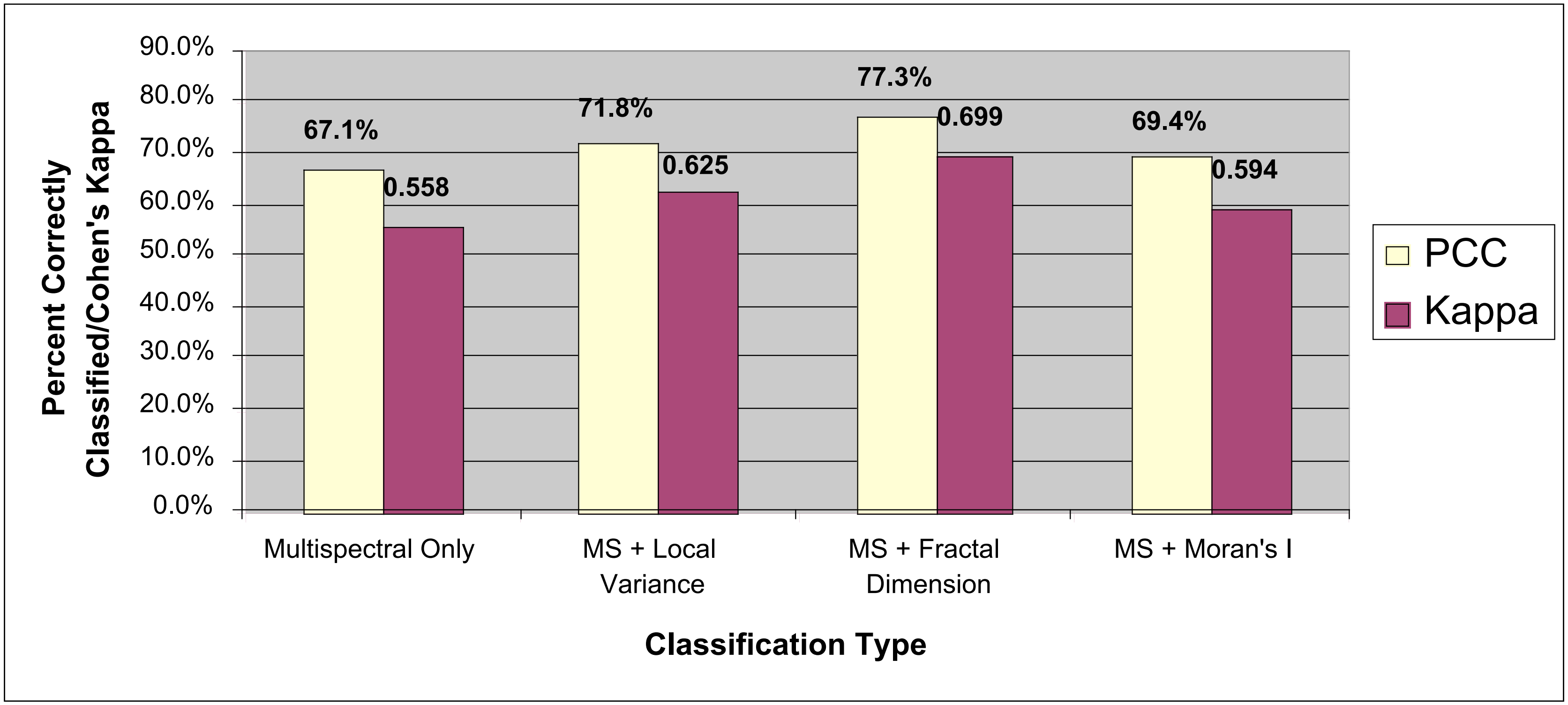

Local Variance


Loc. Fractal Dim.


Local Moran’s I

- Supervised classification accuracies can be improved by including spatial measurements
- Moran’s I is a sensitive indicator of landscape change in a binary sense
  - Separability of change types is problematic
- Fractal Dimension can be used to classify urban scenes according to surface complexity
- Spectral information is still valuable

Overall Classification Accuracy



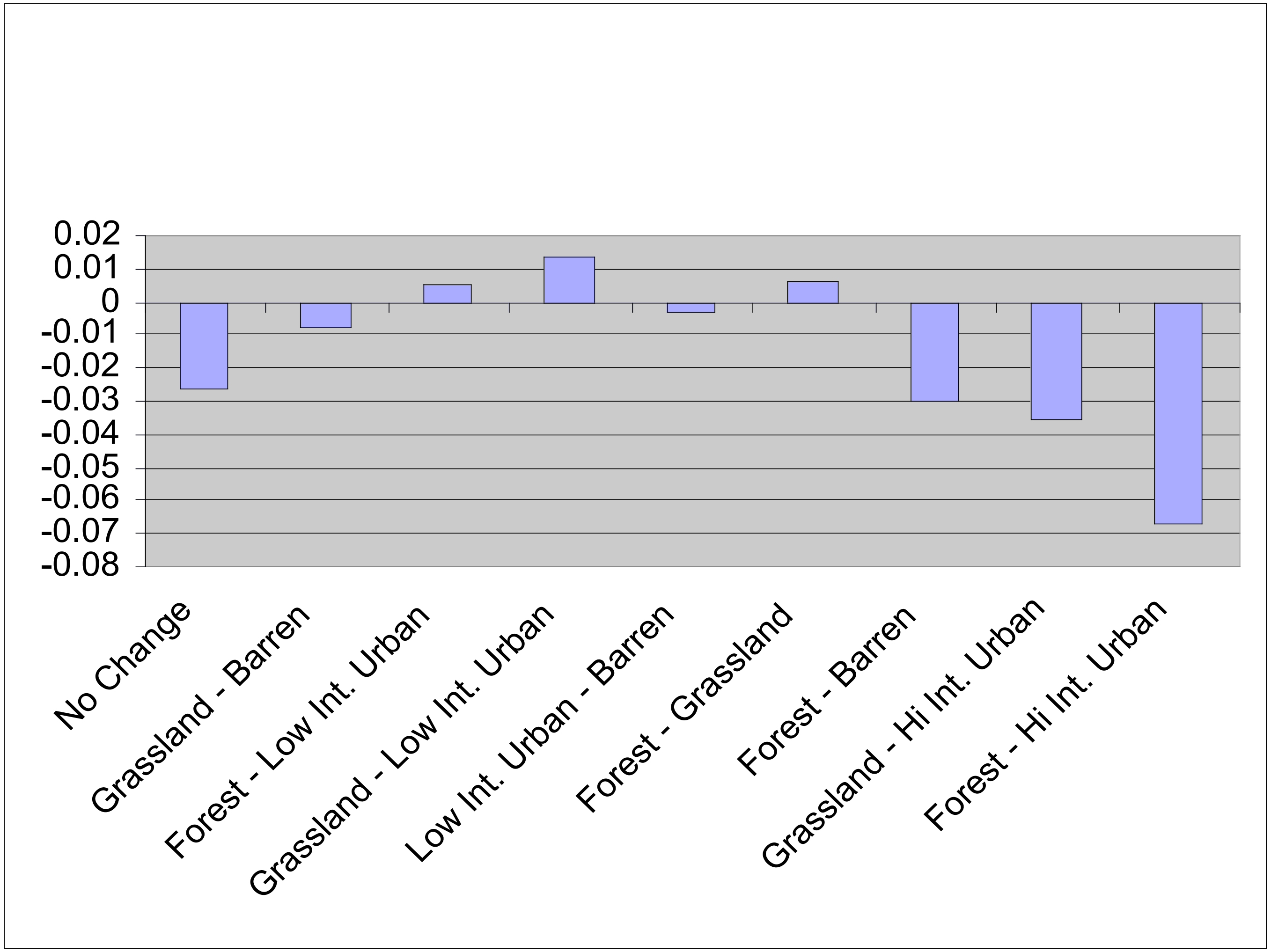
Land Area Estimates

Land cover	Vector LandPro99	LandPro99 30 m raster	MS only	MS + fractal	MS + Moran's I	MS + loc. var.
Hi Int Urban	1100.5	1100.3	1016.1	1028.0	1028.0	1008.1
Pasture	1409.7	1409.4	1609.7	1492.1	2171.2	1706.8
Water	175.1	175.2	349.1	291.6	320.5	383.6
Lo Int Urban	3512.5	3512.5	1764.3	2920.2	1640.2	1916.8
Forest	4245.2	4245.3	5712.6	4719.8	5291.9	5436.3
Total	**10443.0**	**10442.7**	**10451.7**	**10451.7**	**10451.7**	**10451.7**

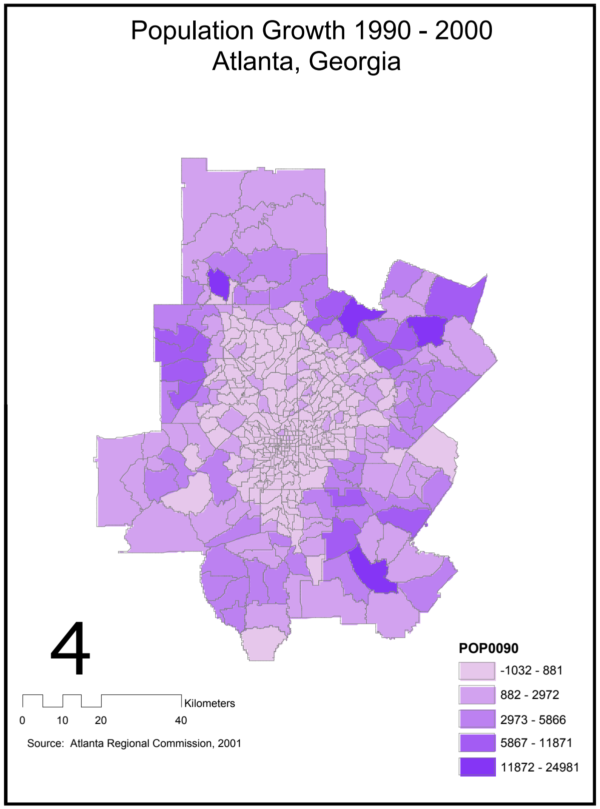
NALC Anthropogenic Land Cover Change

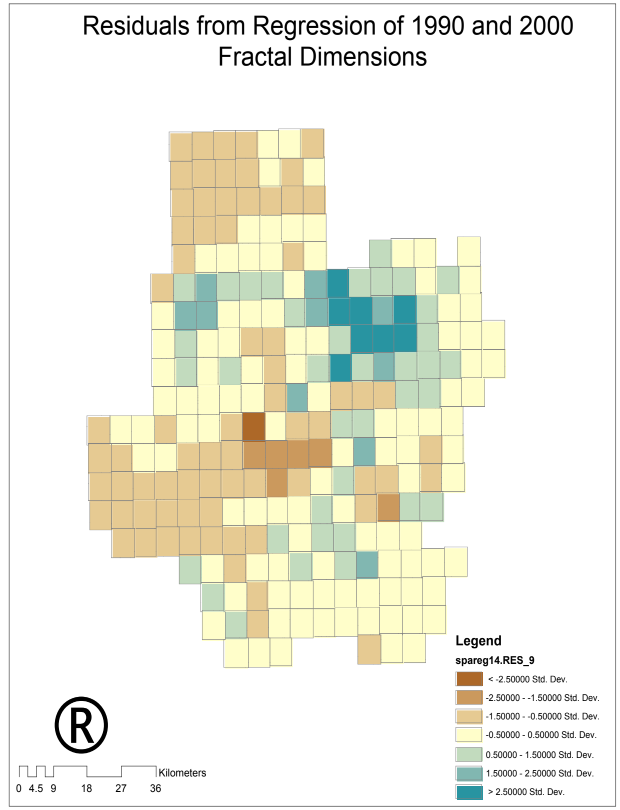
1976 Land Cover	1991 Land Cover
Pasture/Grassland	Low Intensity Urban
Pasture/Grassland	Barren
Pasture/Grassland	Pasture/Grassland
Forest	Low Intensity Urban
Forest	Quarries, Transitional Areas
Low Intensity Urban	High Intensity Urban

Mean Local Fractal Dimension Difference 1976 - 1991



Atlanta Population Growth 1990 - 2000



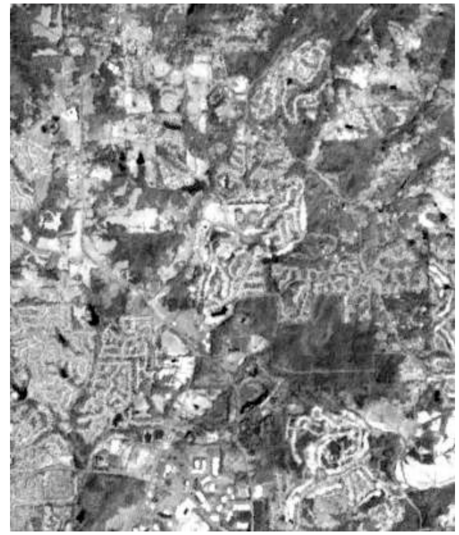


- SPOT^{TM} images from 1990 were resampled to 15 m resolution and registered to 2000 Landsat 7 pan images of USGS quarter quadrangles
- Fractal dimensions for each date were computed for each quarter quad for each date
- The fractal dimension values for the two dates were then regressed on one another

Fractal Dimension as a Content-Based Image Descriptor

Duluth, GA NE Quarter Quadrangle

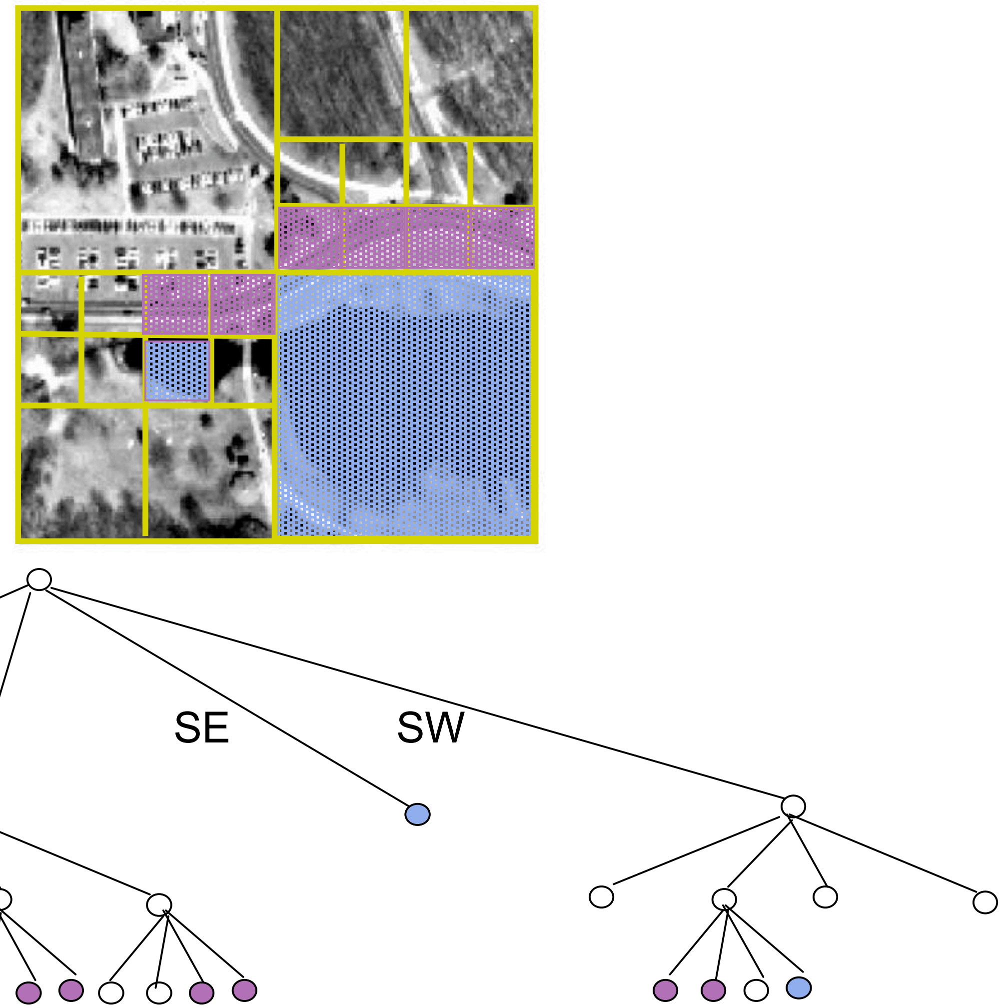
SPOT 1990



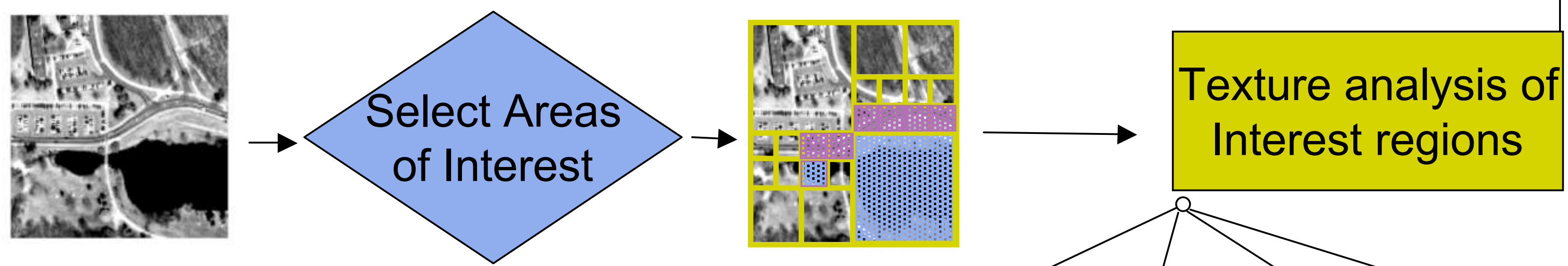
Landsat ETM+ 2000

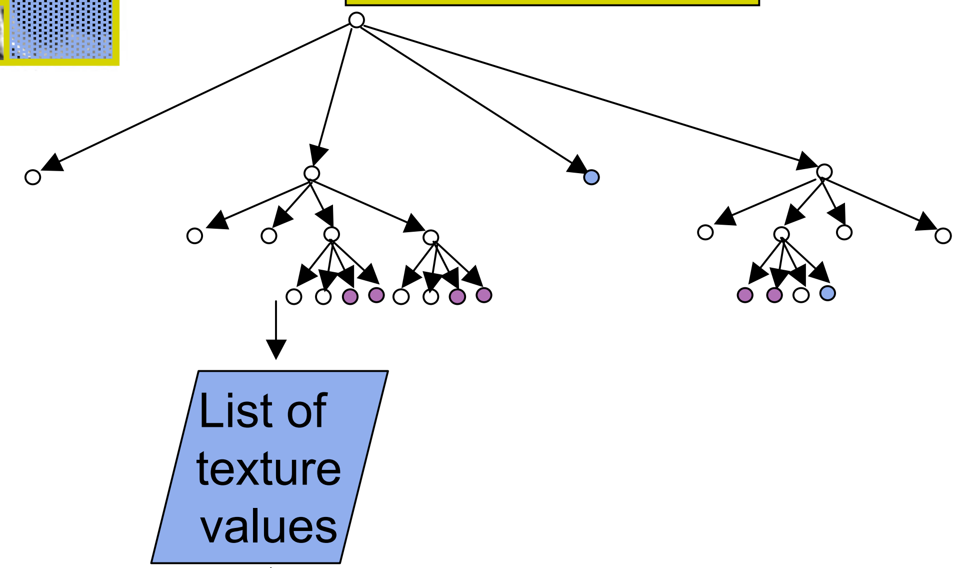
- Residual fractal dimensions of two dates of quarter quadrangle images were only loosely correlated (R^2 = 0.37) to population changes between 1990 and 2000
  - Anthropogenic changes can simplify the texture of an image
    - Replacing forest with industrial/commercial development
  - Development that replaces grassland with housing leads to more complex images
- However, negative residuals were generally associated with large population increases

Spatial Metadata: Quadtree Segmentation

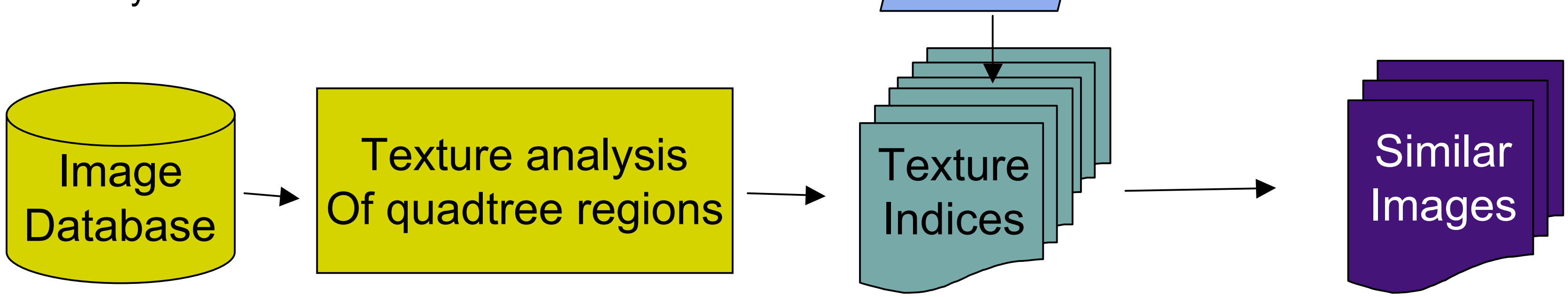


Similarity Search

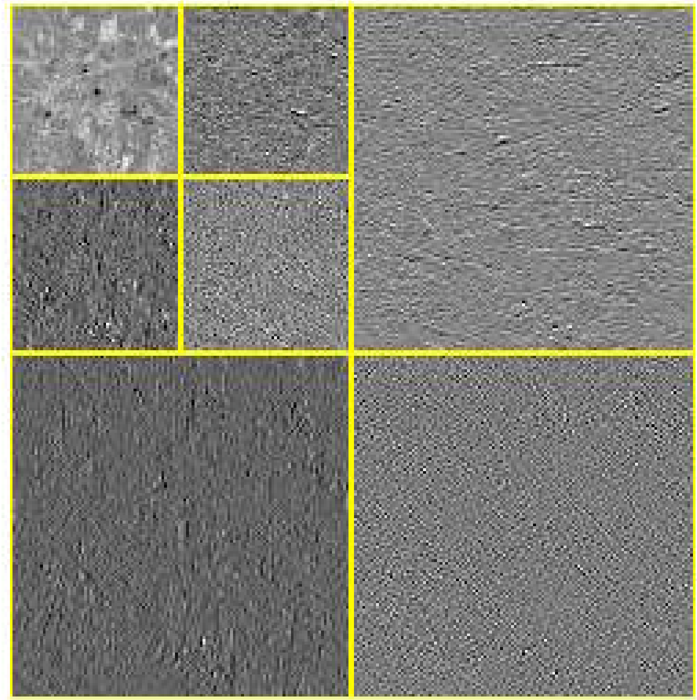




- For database of 238 quarter quadrangle images, texture measures were obtained for quadtree levels 0 – 3
- An example image is segmented by the user to set up a search string
- References to images that match the pattern of texture measures in the example are returned to the user
- Quadtree structure allows topology to be included in the search to increase flexibility



Wavelet Multiresolution Decomposition



Decomposition at level 2

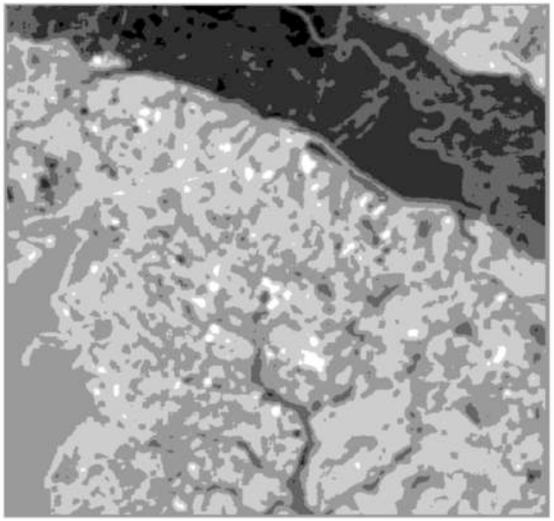
- **Wavelet transform is more accurate than fractal dimension for detecting and characterizing spatial structures.**
  - **A longer wavelet is more accurate;**
  - **The combination of energy signatures from multiple decomposition levels and multispectral bands leads to better image characterization results**

Wavelet-Based Image Segmentation: Hurricane Hugo

Francis Marion National Forest, South Carolina (hit by Hugo Sep. 25, 1989)

Landsat TM
October 14, 1987

Landsat TM
October 11, 1989



Difference between
Level 2 wavelet
energies for
1987 and 1989

- The darkest and the brightest pixels in the difference image signal greatest frequency changes in negative and positive directions, respectively

Notes for Further Research

- Evaluate optimal window sizes and other method parameters
  - Involves space-scale relationships and modifiable areal unit problem
- Examine utility of spatial image descriptors as search indices
- Analyze effects of image processing procedures
  - Band ratioing, resampling, rescaling, radiometric corrections
- Complete the development of the Web interface

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